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State Of Charge Estimation on Lithium-Ion Batteries Using *Quantum Neural Network*

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Abstract

Battery applications can be found in electric vehicles, renewable energy power plants, and various other portable devices. In this final project research, the author utilizes the Quantum Neural Network (QNN) method to estimate the State of Charge (SoC) of a lithium-ion battery designed using Python. This research involves the design of a prototype SoC estimation system for lithium-ion batteries utilizing the QNN method, real-time SoC data collection, and a comparison of SoC estimation performance using QNN with real-time data. The results of real-time testing of lithium-ion batteries using ACS712 voltage and current sensors for five cycles show the following voltage results: first cycle 10.70 V to 12.68 V, second cycle 10.56 V to 12.66 V, third cycle 10.60 V to 12.69 V, fourth cycle 10.60 V to 12.00 V, and the fifth cycle 10.41 V to 12.07 V. Meanwhile, the current sensor results for five cycles showed a range of 0.1 A to 0.5 A. Each test result per cycle showed a higher increase, although there were small fluctuations, and the overall trend line showed the consistency of the voltage sensor's performance without significant degradation during repeated tests, indicating good stability of the voltage sensor. Then, methods with qubit rotation, linear entanglement, and a Neural Network were tested. SoC prediction results using QNN with qubit rotation showed MAPE and RMSE values of 0.14 and 61%, respectively. Furthermore, testing the SoC prediction results on QNN with linear entanglement shows MAPE and RMSE values of 0.08 and 29%, respectively. While the SoC prediction results.

Keyword: Battery, Lithium Ion, State of Charge, Quantum Neural Network, Neural Network, Sensor

1. Introduction

In today's technological era, batteries are integral to various aspects of daily life, powering electric vehicles, renewable energy power plants, mobile phones, laptops, and other portable devices (Siahaan et al., 2021). The preference for batteries stems from their reliability as a power source for numerous portable technologies. For smart city applications, secondary batteries, known for their rechargeability, are particularly in demand (Siahaan et al., 2021). Despite their widespread use, batteries present several challenges, including limited power storage capacity, restricted power distribution, and a relatively short lifespan (Rahmawan, 2018). These drawbacks are contingent on the type and characteristics of each battery. Inefficient battery use, often due to excessive use, is a common issue. Understanding battery capacity is crucial for extending battery life, with the State of Charge (SoC) being a pivotal metric indicating available energy (Tyesadha, 2018). SoC, the ratio of remaining energy to the maximum energy capacity of the battery, is expressed as a percentage from 0% to 100% (Rahman, 2018). Accurate SoC estimation is vital to prevent system damage, overcharging, and overdischarging, which can cause permanent damage (Rahman, 2018). This study aims to estimate SoC using the Quantum Neural Network method, leveraging advancements in quantum computing and machine learning.

Monitoring batteries is complex due to the intricate chemical reactions involved. The battery cycle, encompassing charging, displays two key measured parameters: current and voltage. These measurements integrate the SoC parameters. This research employs Lithium-Ion batteries to compare SoC data results using the Quantum Neural Network method with real-time data, aiming to identify the superior method for SoC estimation in Lithium-Ion batteries (Chen et al., 2023).

The application of machine learning algorithms, such as neural networks, has shown promise in SoC estimation for Lithium-Ion batteries (Chandran et al., 2021). Feed-forward backpropagation neural networks are particularly effective in this context (Aisyah et al., 2020). Similarly, Quantum Neural Networks offer a novel approach for more accurate SoC estimation (Ngo et al., 2023). Quantum computing methods, including Quantum Neural Networks, have gained attention for their potential in various applications, such as battery management (Kulkarni et al., 2021; Kuppusamy et al., 2022). Integrating quantum machine learning with battery technology could revolutionize SoC estimation and management (Biamonte et al., 2017). Accurate SoC estimation is critical for the optimal performance and longevity of batteries. The Quantum Neural Network method, with its advanced computational capabilities, holds significant promise for improving SoC estimation accuracy. This research contributes to the ongoing development and innovation in battery technology, with implications for smart cities and various portable technology applications (Zhang & Ni, 2020; Vidal et al., 2020).

Moreover, the development of quantum computing and machine learning methods, such as Quantum Neural Networks and Quantum Convolutional Neural Networks, has opened new avenues for battery research and management (Cong et al., 2019). These advanced methods enhance the precision of SoC estimation, thus improving battery performance and lifespan (Ng et al., 2023). Several studies have demonstrated the effectiveness of neural network algorithms in SoC estimation. For instance, Aisyah et al. (2020) employed feed-forward backpropagation neural networks for Lithium-Ion batteries, showing promising results. Similarly, Chandran et al. (2021) utilized machine learning algorithms for electric vehicle batteries, achieving high accuracy in SoC estimation.

Furthermore, the synergy of machine learning and quantum computing offers unprecedented opportunities for battery management. Kulkarni et al. (2021) and Kuppusamy et al. (2022) highlighted the potential of quantum machine learning in enhancing the accuracy and efficiency of battery management systems. This study's focus on the Quantum Neural Network method for SoC estimation aims to bridge the gap between theoretical advancements and practical applications in battery technology. By comparing real-time data with Quantum Neural Network estimates, this research seeks to validate the method's superiority in SoC estimation for Lithium-Ion batteries (Ngo et al., 2023). In addition to improving SoC estimation, advancements in quantum computing can enhance other aspects of battery technology. For example, Rahman (n.d.) discusses how quantum computing poses new challenges and opportunities for cryptographic systems, which could also apply to secure battery management systems. Similarly, Tychola et al. (2023) provide an overview of how quantum machine learning can be applied to various engineering fields, including energy systems.

In conclusion, the accurate estimation of SoC is essential for maintaining battery performance and extending its lifespan. The Quantum Neural Network method, underpinned by advancements in quantum computing and machine learning, offers a promising solution for improving SoC estimation accuracy. This research not only contributes to battery technology development but also has broader implications for smart cities and portable technology applications (Zhang & Ni, 2020; Vidal et al., 2020).

2. Method

The research methodology is presented in the form of *a flowchart* as a structured and systematic procedural flow.

2.1. Research procedure

At this stage, the methodology in the research will be explained, including problem identification, literature study, system design, and system testing.

2.1.1 Literature Studies

Literature studies are important in the search and study of relevant and reliable sources. The sources used come from national and international journals as well as books on the theme of lithium-ion batteries and quantum neural networks.

2.1.2 Problem Identification

The determination of problem identification begins with conducting appropriate battery modeling to describe conventional battery actual data to measure state of charge (SOC) parameters, actual data is carried out by looking at the results of data collection and data processing to compare the data results from the state of charge using the quantum neural network method with measurement data in real time To find out the difference and it can also be known which is the superior method to estimate the state of charge in lithium ion batteries. The battery is given input from voltage and current based on the provisions of the lithium battery specification.

2.1.3 Charge System Design

The design of the research will be explained in the form of a block diagram that illustrates the steps of how this research will be conducted. The hardware design scheme for the estimated *state of charge* in lithium-ion batteries and the *input* and *output processes* in the diagram blocks are as follows.

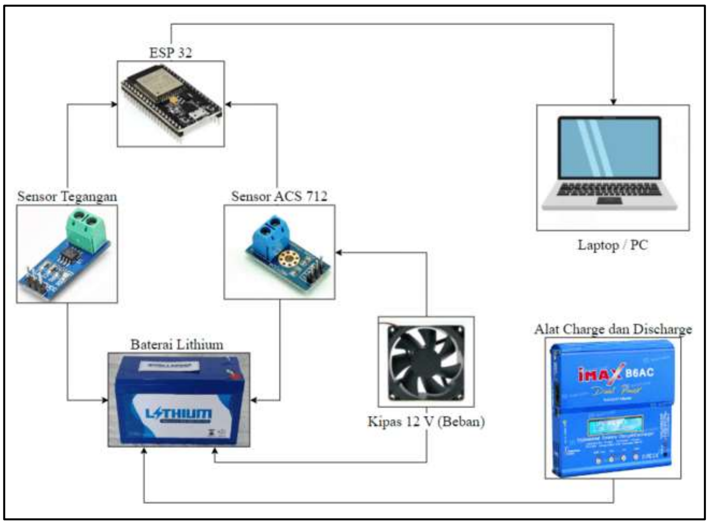

Figure 1: Hardware Design Scheme

This process begins with the battery to the layout scheme of the sensor used. In this case, the sensors used are 2 sensors. The former uses voltage sensors and ACS712 to measure current and voltage. Then the data obtained from several current and voltage sensors will be processed using the ESP32 microcontroller. After the data is received by the ESP32, it will get data that is then processed to determine the State Of Charge (SOC).

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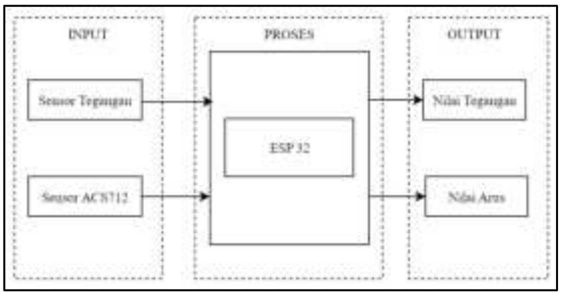

Figure 2: Block System Diagram

The time, current, and voltage obtained from each sensor serve as the variables measured. The microprocessor will process the variables obtained from each sensor, then generate *a state of charge* (SoC) as the output of the process. In addition to design, another important component is simulation modeling. Simulation modeling aims to model a monitoring system for SoC value calculations. This modeling includes the charging and discharging conditions of the battery. The purpose of simulation modeling is to provide an initial idea of how the system works before the tool is created.

2.2. Proses Quantum Neural Network

The *Quantum Neural Network* process is the stage in processing the estimated state of charge data on the battery as follows.

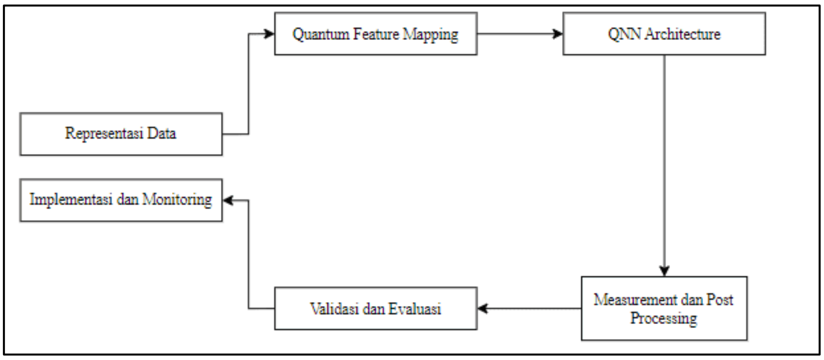

Figure 3: Flow Diagram of the QNN Method Process

Flow Diagram of the Quantum Neural Network (QNN)

1. **Data Representation**: The data used for SoC estimation, such as voltage, current, temperature, and battery historical data, is converted into a format that can be processed by QNN. This data is then encoded into qubits, the basic unit of information in quantum computing.
2. **Quantum Feature Mapping**: This process involves using quantum gates to transform input data into higher quantum feature spaces, allowing for capturing more information and correlations that may not be visible in classical feature spaces.
3. **QNN Architecture** :
- **Quantum Layers**: Similar to the layers on classical neural networks, QNNs have quantum layers that consist of a series of quantum gates that change the state of qubits.
- **Parameter Optimization**: Parameters in quantum gates are optimized during the training process to minimize errors between the predicted output and the actual value of the SoC. This is done through quantum optimization algorithms, such as Gradient Descent, which are adapted for the quantum domain.
4. **Measurement and Post Processing**: Train QNN with historical data. This process involves iterative iterations to optimize the model's parameters by using appropriate optimization algorithms.
5. **Validation and Evaluation**: Validate the QNN model by using a separate dataset that is not used in training. Metrics such as MAPE and RMSE are used to evaluate model performance.

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6. **Implementation and Monitoring**: Once deemed adequate, the QNN model can be implemented on the actual battery system to perform SoC estimation.

3. Results and Discussion

In the formation of this Lithium Ion battery, 4 lithium battery cells are used, which use input parameter specifications in the form of voltage of 12 V and current of 8.4 Ah, and battery specifications based on the table are applied in the measurement of batteries in real time.

Table 1: Lithium Battery Model

Lithium Cell	Information
Nominal *Voltage* (V)	12 V
Rated Capacity (Ah)	8.4 Ah / 8000 mAh
Fully Charged Voltage (v)	12.50
Cut-Off Voltage	10.50

Figure 4: Lithium Battery Model

The battery model is useful for regulating specific selections and operating conditions used in those simulated measurements. Battery cells that have been formed based on these specificities can be used to monitor and control the state of charge condition. The characteristics of the minimum current discharge are in accordance with the choice of lithium battery, which has a nominal capacity of 8.4 Ah and a nominal voltage of 12 V. The following battery models used in the state of charge measurement can be seen based on Figure 5.

The results and discussion explained the results of the research and analysis related to the application of the quantum neural network method of lithium batteries and the results of real-time lithium battery measurements that have been designed according to expectations, namely, being able to get SOC output in lithium batteries. From the implementation of data training that has been carried out through *the Google Colab* software.

Figure 5: Prototype Design Results

Figure 5 is a schematic of the entire system that has been designed and used in this study. In general, it consists of an SoC monitoring instrument, a 12 V fan as a load, an Imax B6AC dual power as a battery *charge/discharge* system, and a laptop as a data monitoring using (PLX DAQ). And the image above is also a monitoring instrument of the system that uses several components, such as ESP 32 as a microcontroller, ACS 712 sensor as a current reading indicator, and a voltage sensor as a voltage reading indicator.

3.1. State Of Charge Value Results In Real Time

After obtaining the voltage and current values from the *real-time measurement results* on the lithium battery, it is possible to validate the SoC relationship and predict the SoC value in *real time* under the condition of *the battery charge*. The voltage and current values measured in *real time* are used to predict the results of the SoC when the battery is in use. The relationship test was carried out by discharging the battery from 12.69 volts to 10.41 volts according to the datasheet with a load of 12 V, and data sampling was carried out every 1 minute. The SoC is done to know and ensure that the voltage is measured in proportion to the *state of charge* of the lithium battery. The graph of the state *of charge prediction test* results on lithium batteries for five cycles is shown in the figure below.

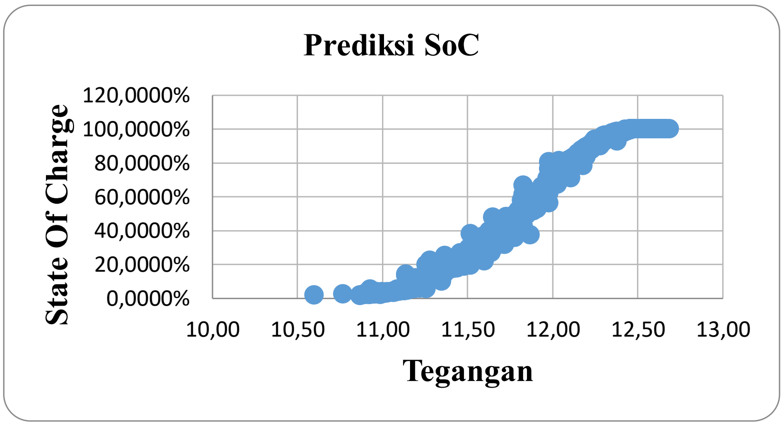

Figure 6: SoC prediction on the battery

The SoC prediction results on lithium batteries for SoC estimation in *real time* state that the results of the voltage sensor graph image ranging from one cycle to five cycles above on the x-axis, we have an SoC value that may represent the measurement point, while the y-axis indicates the sensor voltage value. It can be seen that the sensor voltage value tends to increase with the passage of time or measurement point. The graph above also describes the performance of the voltage sensor over one to five test cycles, which can be used to describe the stability, accuracy, or other characteristics of the sensor.

3.2. State Of Charge Testing with the Quantum Neural Network Method

After conducting the lithium battery testing stage in *real time*, the method testing stage is carried out to determine the level of accuracy and prediction in the modeling of the QNN method that has been designed. The following are some of the stages of testing that were carried out, namely, testing the results of SoC prediction on QNN with qubit rotation and linear entanglement.

3.2.1 Testing the State Of Charge Prediction Results on a Quantum Neural Network with Qubit Rotation

The results of state *of charge prediction* on *quantum neural networks* with qubit rotation, which aims to improve the accuracy of SoC prediction in lithium-ion batteries. The rotation of qubits in *quantum neural networks* allows for faster and more efficient data processing. This research involves measuring two main parameters, namely current and voltage, during the battery charge and discharge cycle. The data from these measurements is used as input in the *Quantum Neural Network* to estimate the SoC value. The accuracy of the predictions is then compared with real-time data to evaluate the performance of this method.

The test results show that *the Quantum Neural Network* with qubit rotation can generate highly accurate SoC predictions, close to real-time data. The use of qubit rotation in this model not only improves the prediction precision but also significantly reduces the computational time. The following is a qubit rotation test shown in the figure below.

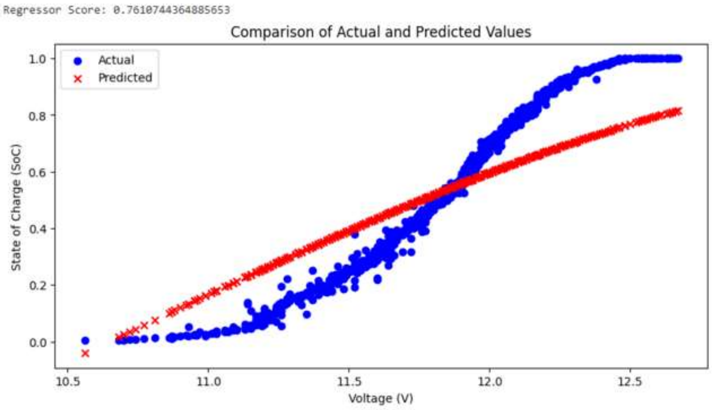

Figure 7: SoC prediction on QNN with qubit rotation

This graph plots two data sets labeled 'Actual' and 'Prediction,' represented by a red cross and a blue dot, respectively. This data is plotted on two axes: the horizontal axis labeled 'Voltage (V)' with a value range between about 10 to 12.5, and the vertical axis labeled '*State of Charge* (SoC)' with a value range between 0 and 1.0. The graph shows that as the voltage increases, the SoC values also increase for both the actual and predicted values, although they show similar patterns but do not completely overlap. This graph is interesting because it compares experimental data or observations ('Actual') with the model or expected outcome ('Prediction'). In the upper left corner of the image, there is a regression score that shows "Regression Score: 0.7610743488468553," indicating that a regression analysis has been performed to evaluate how well the predicted value corresponds to the actual value.

Table 2: *QNN Performance Testing with Qubit Rotation*

RMSE	MAPE
0.14	61. %

It can be seen that when using qubit rotation, the resulting MAPE and RMSE values are 0.14 RMSE values, as well as 61% of the value of MAPE. The RMSE value of quantum *neural networks* for qubit testing is greater than the MAPE value of neural *networks* due to the complexity of uncertainty models in *quantum computing* and quantum technology that are still in the development stage.

3.2.2 Testing of State of Charge Prediction Results on Quantum Neural Network with Linear Entanglement

Furthermore, the test of SoC prediction results on QNN with linear entanglement aims to assess the accuracy of the QNN model in predicting battery SoC using linear entanglement techniques. This technique utilizes quantum correlation to improve the efficiency and accuracy of predictions. This study measures two main parameters, namely current and voltage, during five battery charging and discharging cycles. The data obtained from these measurements is used as input in the QNN to estimate the SoC value. The evaluation is carried out by comparing the prediction results with real-time data to assess the model's performance.

The test results show that QNN with linear entanglement is able to produce highly accurate SoC predictions, close to real-time data. The linear entanglement technique not only improves the accuracy of predictions but also significantly reduces the computational time. The following is a linear entanglement test shown in the figure below.

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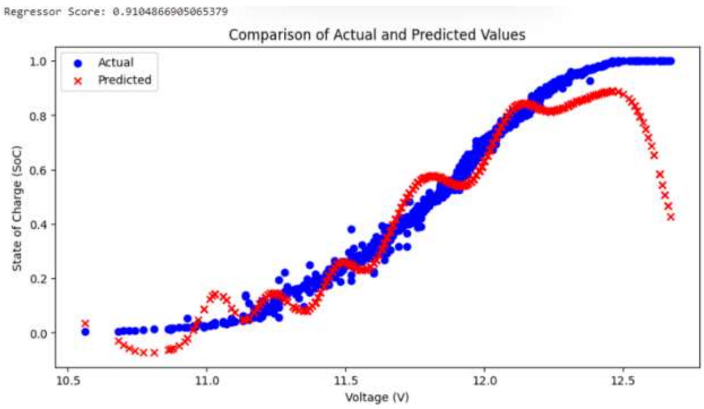

Figure 8: SoC prediction on QNN with *Entanglement Linear*

On thehorizontal axis (X), we see the voltage value in volts that ranges from 10.5 to 12.5, while on the vertical axis (Y), the SoC value is displayed in percentages, ranging from 0.0000% to 120.0000%. The blue dots represent the actual value of the SoC, while the red cross represents the predicted value of the SoC. Both data sets show a similar trend: the higher the voltage, the higher the SoC value, which illustrates the positive correlation between voltage and SoC. In conclusion, a model or method that generates SoC predictions that are close to the actual value gives good results.

Table 3: QNN Performance Testing with Linear Entanglement

RMSE	MAPE
0.08	29. %

Table 3 shows the relationship between the prediction values of *the quantum neural network* and the MAPE and RMSE values generated in the test. It can be seen that when using qubit rotation, the resulting MAPE and RMSE values are 0.08 RMSE values, as well as 29% of the values from MAPE. The MAPE and RMSE values in quantum *neural networks* for linear entanglement testing are smaller than the MAPE values for qubit rotation testing because linear entanglement offers a more appropriate and appropriate approach to a particular problem, which causes the RMSE values to be lower compared to qubit rotation in QNN.

3.2.3 Testing State Of Charge Prediction Results on Neural Networks

The results of state *of charge* prediction in NN are an innovative approach in estimating the battery charge rate at a certain time using concepts from quantum physics and neural networks. This approach aims to improve the accuracy and performance of SoC estimation, especially when it comes to handling complex battery estimates and behaviors that are difficult to model conventionally. The following graph of the results of the *prediction of the state of charge* on the *neural network.*

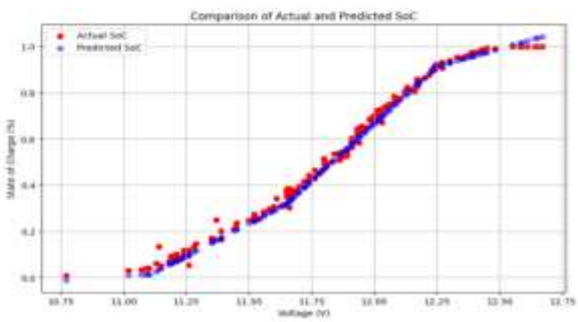

Figure 9: SoC Prediction on NN

Figure 8 is a graph that compares the actual *state of charge* and the prediction based on voltage. It should be noted that the red dot is the actual SoC, while the blue dot is the predicted SoC. The two data sets appear to be very close to each other, suggesting that SoC predictions are very accurate. This graph also shows the relationship between battery voltage and SoC estimation. On the x-axis is the voltage value (in volts), while on the y-axis is the SoC estimate (in percentage). It should be noted that the two data sets almost rest on a diagonal line, indicating a good fit between actual and predicted SoCs.

Table 4: NN Performance Testing

RMSE	MAPE
0.01	6 %

Table 4 shows the relationship between the neural network prediction value and the MAPE and RMSE values generated in the test. It can be seen that when using qubit rotation, the resulting MAPE and RMSE values are 0.01 RMSE values, as well as 6% of the MAPE values. MAPE and RMSE values in neural *networks* seem to be lower and better than MAPE and RMSE values in *quantum neural networks* due to the use of simpler and more stable architectures.

3.2.4 Comparison of SoC Estimated Performance using Quantum Neural Network compared to Real Time

Estimating a battery's State of Charge (SoC) is an important process for measuring the amount of energy left in a battery. The two approaches used for SoC estimation are using a *Quantum Neural Network* (QNN) and real-time measurements. A comparative analysis of the performance of these two approaches involves evaluating the accuracy, efficiency, and reliability of the resulting SoC estimates as follows.

Table 5: Comparison Estimates of *Quantum Neural Network* and *Real-time*

Comparison		
Accuracy	QNN: Generally more accurate under varying conditions because it can learn historical patterns and be adaptive to changes in battery conditions.	*Real Time*: Accuracy can be affected by environmental conditions and sensor quality, and is more susceptible to noise.
Efficiency	QNN: After the initial training, SoC prediction can be done very quickly and efficiently.	*Real Time*: Requires continuous measurement that can increase power consumption and data processing needs directly.
Reliability	QNN: More reliable in the long run because it can adapt to changing usage patterns and battery degradation.	Real *Time*: Depends on the quality and condition of the sensor. Sensors that are degraded may reduce the reliability of measurements.

In the table above, it can be concluded that the use of *Quantum Neural Network* (QNN) for State *of Charge* (SoC) estimation offers advantages in terms of prediction accuracy and reliability, especially in the long term and various operating conditions. Although real-time measurements provide immediate and fast information regarding the SoC, this method is more susceptible to accuracy and reliability issues affected by environmental conditions and sensor quality. Therefore, integrating QNN with *real-time* can provide an optimal solution, where QNN provides more stable predictions while real-time measurements ensure direct monitoring of battery health.

3.2.5 Comparison of SoC Estimation Performance using Quantum Neural Network compared to Neural Network

Comparison of the estimated performance of State of Charge (SoC) using *Quantum Neural Network* (QNN) compared to *Neural Network* (NN) can be evaluated based on several performance parameters such as accuracy, speed, computational complexity, and generalization ability. Here is the comparison.

1) *Accuracy*
   - ***Neural Network*** **(NN)**: Traditional NNs have been proven to provide fairly accurate SoC estimation with the right dataset and good preprocessing. They are capable of handling the non-linear relationship between battery parameters and the SoC.
   - ***Quantum Neural Network*** (QNN): QNNs have the potential to further improve accuracy through quantum processing, which can handle nonlinear and high complexity computing more efficiently than traditional NNs. QNN can be better at finding invisible patterns in large and complex data.

2) *Computing Speed*
   - ***Neural Network*** (NN): With today's hardware, NNs can be trained and executed in a relatively fast time using GPUs or TPUs.
   - ***Quantum Neural Network*** (QNN): QNNs, when implemented on quantum computers, can offer much higher computational speeds in theory, especially for problems involving optimization and search in high-dimensional spaces. However, at present, the practical speed of QNN is limited by the capabilities of quantum hardware that is still in the development stage.

3) *Computational Complexity*
   - ***Neural Network*** (NN): The computational complexity of NNs increases with the number of layers and neurons. NN training can be lengthy and requires significant computing resources.
   - ***Quantum Neural Network*** (QNN): QNN is expected to have lower computational complexity in some specific cases, due to the exponential nature of quantum computing. However, for now, developing and implementing QNNs is still a major challenge and requires specialized knowledge in the field of quantum computing.

4) *Generalization Ability*
   - ***Neural Network*** (NN): NNs can overfit if not trained properly. However, with techniques such as regularization and cross-validation, the generalization capabilities of NNs can be improved.
   - ***Quantum Neural Network*** (QNN): QNN has the potential for better generalization thanks to its ability to handle the complexity and high variety of data. The superposition and interference capabilities in quantum computing allow QNN to explore more possible solutions simultaneously.

5) *Development and Implementation*
   - ***Neural Network*** (NN): NN is very mature in terms of frameworks, algorithms, and supporting hardware. Tools like TensorFlow, PyTorch, and Keras make NN development easier and more affordable.
   - ***Quantum Neural Network*** (QNN): The development of QNN is still in its early stages. Frameworks and tools for QNN are still developing, such as IBM's Qiskit, and are not as mature as tools for NNN. QNN implementation also requires access to quantum computers that are not yet widely available.

4. Conclusion

In this study, the design of a prototype system used to determine the estimated *state of charge* (SoC) in lithium-ion batteries with the *quantum neural network* method is to uses tools including an ESP 32 microcontroller, a voltage sensor, an ACS712 sensor, a 12 V fan, an imax b6AC, and a laptop. Based on the above testing of the QNN method, it shows that currently, *Neural Networks* (NN) are a more implementable and reliable option for estimating *the State of Charge* (SoC) in batteries in real-world situations. However, *Quantum Neural Networks* (QNNs) show great potential for the future, especially if quantum technology-related barriers can be overcome. With the completion of these challenges, QNN can provide a significant improvement in performance and efficiency in SoC estimation in batteries. Lithium battery test results In *real time* using the ACS712 voltage sensor and current sensor for five cycles, it can be concluded that the charging voltage variation over five cycles: the first cycle is 10.70 V to 12.68 V, the second cycle is 10.56 V to 12.66 V, the third cycle is 10.60 V to 12.69 V, the fourth cycle is 10.60 V to 12.00 V, and the fifth cycle is 10.41 V to 12.07 V. ACS712 current sensor test, after calibration by comparing the readings of the microcontroller and multimeter using a power supply and a 12V fan, it shows that the charging current decreases as the voltage increases. In other words, the higher the voltage applied, the less current is detected. This study presents a comparison of the performance of SoC estimation using QNN compared *to real-time.* The use of *Quantum Neural Network* (QNN) for *State of Charge* (SoC) estimation offers advantages in terms of prediction accuracy and reliability, especially in the long term and various operating conditions. Although real-time measurements provide immediate and fast information regarding the SoC, this method is more susceptible to accuracy and reliability issues affected by environmental conditions and sensor quality. Therefore, integrating QNN with *real-time* can provide an optimal solution, where QNN provides more stable predictions while real-time measurements ensure direct monitoring of battery health.

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